

# The Golems of Science

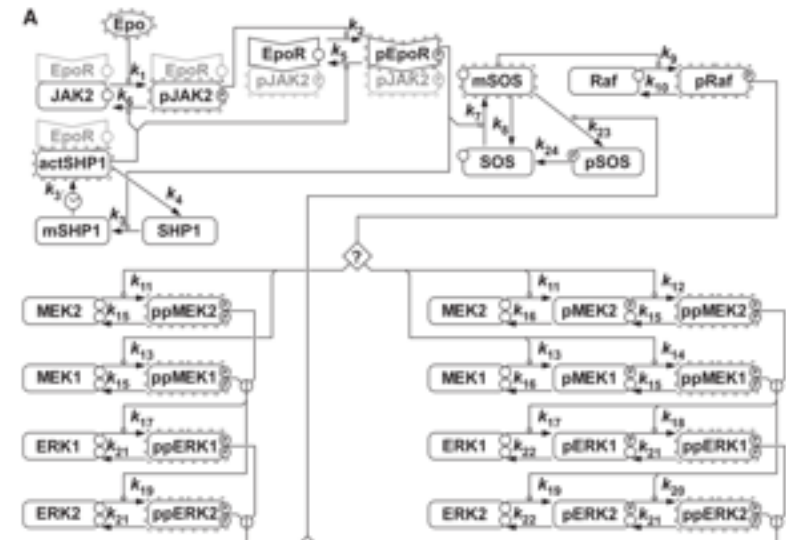
## Golem

- Made of clay
- Animated by “truth”
- Powerful
- Blind to creator’s intent
- Easy to misuse
- Fictional



## Model

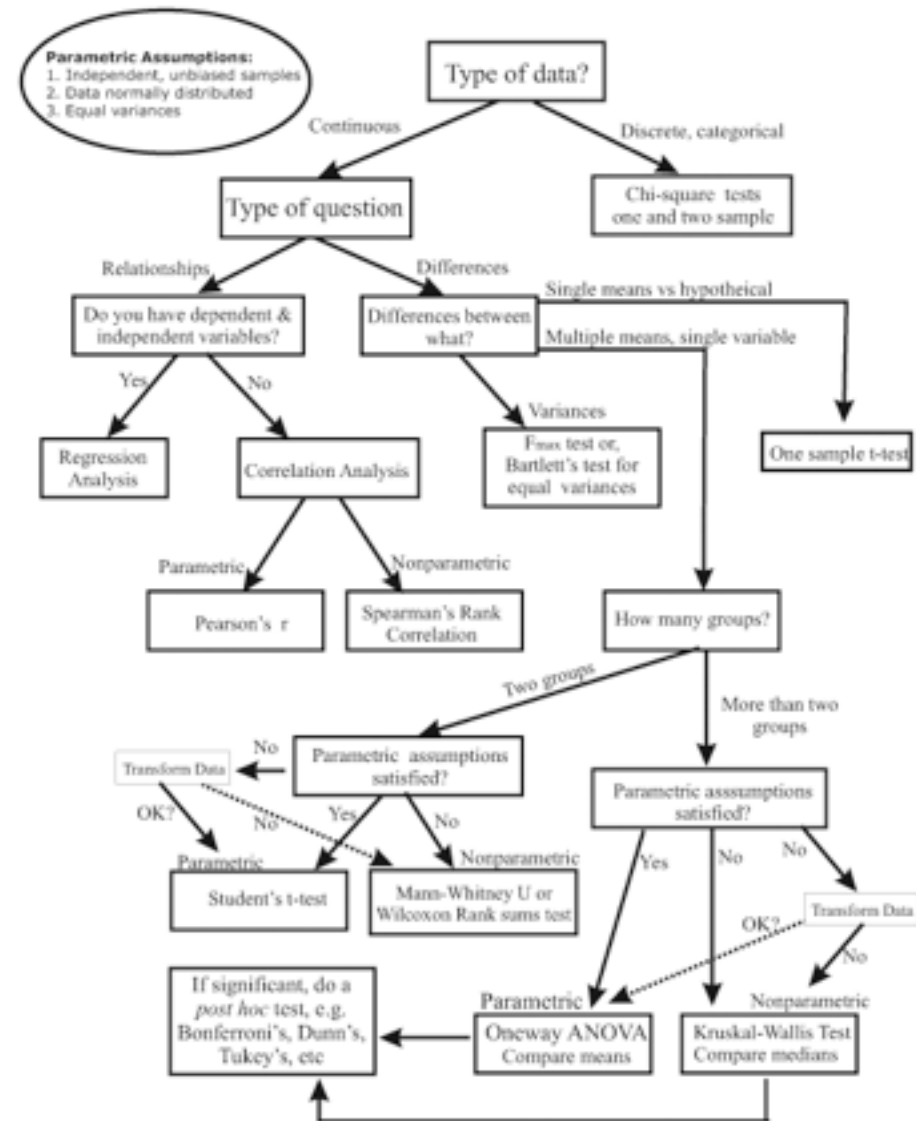
- Made of...silicon?
- Animated by “truth”
- Hopefully powerful
- Blind to creator’s intent
- Easy to misuse
- Not even false



# Against Tests

- Specialized, pre-made golems, “procedures”
- Most developed in early 20th century, fragile, eclipsed by more recent tools
- Users don’t know they are using models (golems)
- Falsifying *null* model not sufficient
- Inference is not decision

Flow Chart for Selecting Commonly Used Statistical Tests



*O, that way madness lies*

# Golem Engineering

- Need a framework for developing and vetting statistical golems
- Several options
- We'll use this one
  - Bayesian data analysis
  - Multilevel modeling
  - Model comparison



*From Breath of Bones: A Tale of the Golem*

# Bayesian data analysis

- Use *probability* to describe uncertainty
  - Extends ordinary logic (true/false) to continuous *plausibility*
- Computationally difficult
  - Markov chain Monte Carlo (MCMC) to the rescue
- Used to be controversial
  - Ronald Fisher: Bayesian analysis “must be wholly rejected.”



Pierre-Simon Laplace (1749–1827)



Sir Harold Jeffreys (1891–1989)  
with Bertha Swirles, aka Lady  
Jeffreys (1903–1999)

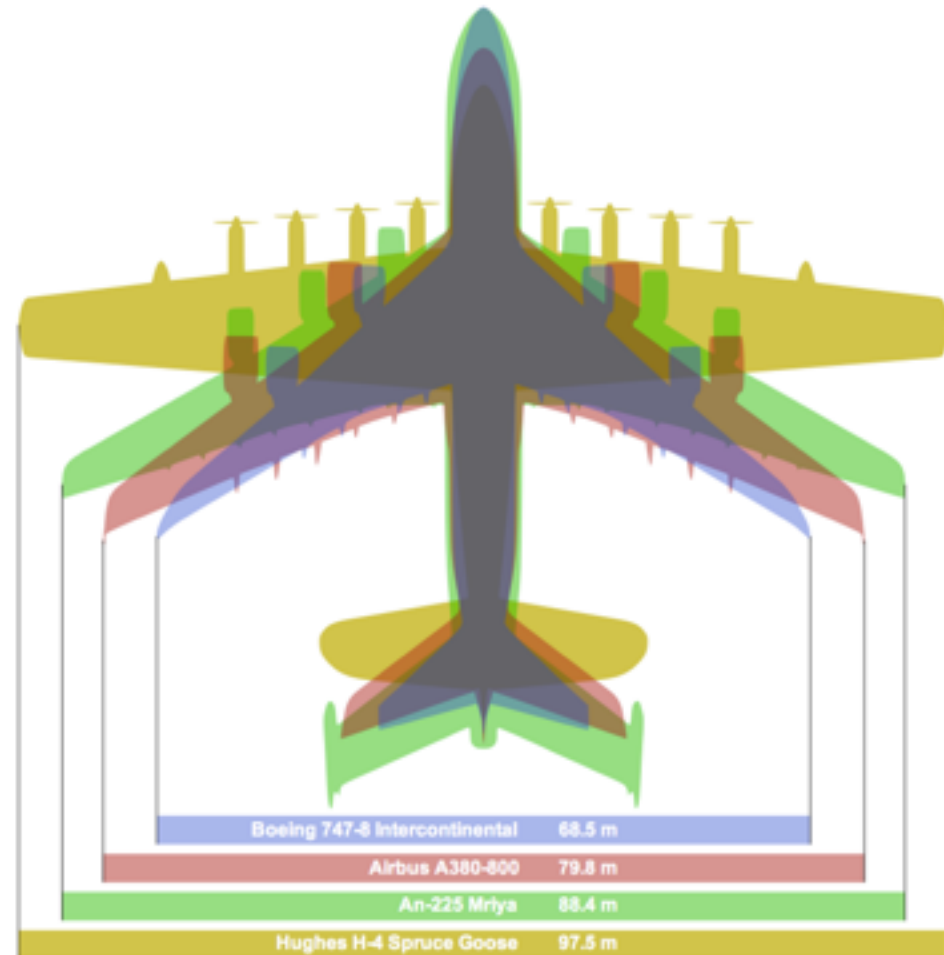
# Multilevel models

- Models with *multiple levels* of uncertainty
  - Replace parameters with models
- Common uses
  - Repeat & imbalanced sampling
  - Study variation
  - Avoid averaging
  - Phylogenetics, factor and path analysis, networks, spatial models
- Natural Bayesian strategy



# Model comparison

- Instead of falsifying a **null** model, compare **meaningful** models
- Basic problems
  - Overfitting
  - Causal inference
- Ockham's razor is silly
- Information theory less silly
  - AIC, WAIC, cross-validation
- Must distinguish prediction from inference



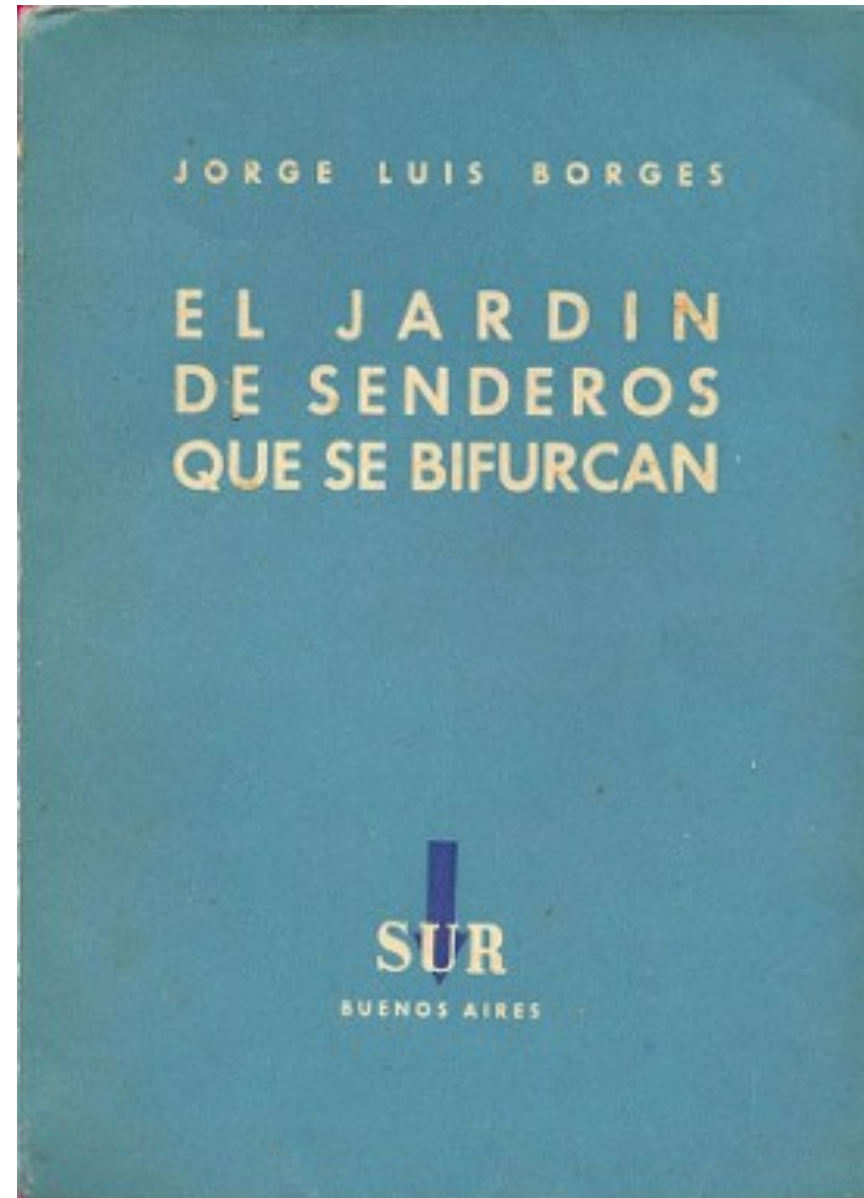
# Bayesian data analysis

*Count all the ways data can happen, according to assumptions.*

*Assumptions with more ways that are consistent with data are more plausible.*

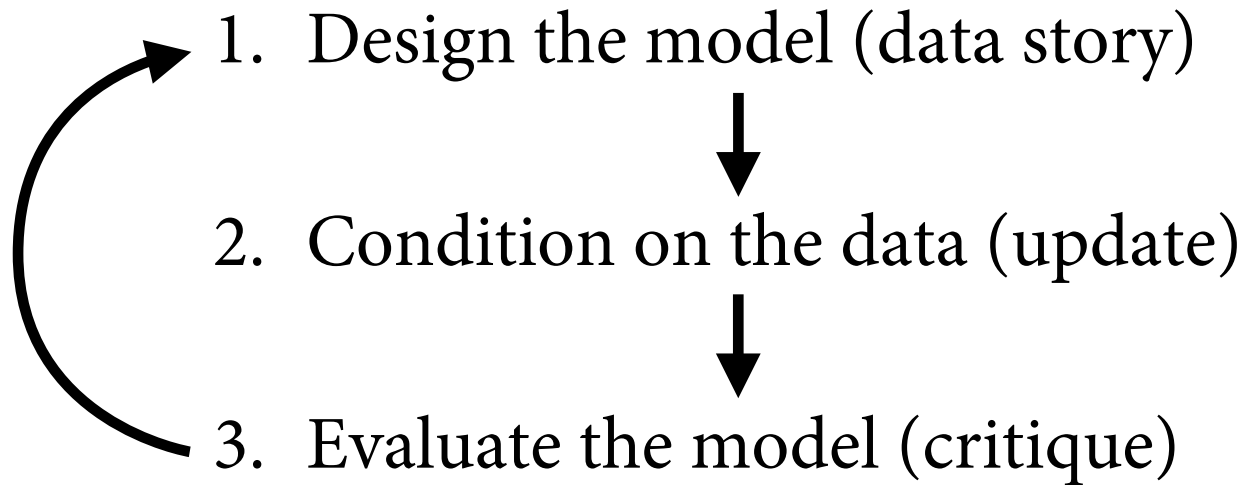
# Garden of Forking Data

- The future:
  - Full of branching paths
  - Each choice closes some
- The data:
  - Many possible events
  - Each observation eliminates some



# Building a model

- How to use probability to do typical statistical modeling?





Nine tosses of the globe:

W L W W W L W L W

# Design > Condition > Evaluate

- Data story motivates the model
  - How do the data arise?
- For **W L W W W L W L W**:
  - Some true proportion of water,  $p$
  - Toss globe, probability  $p$  of observing W,  $1-p$  of L
  - Each toss therefore independent of other tosses
- Translate data story into probability statements

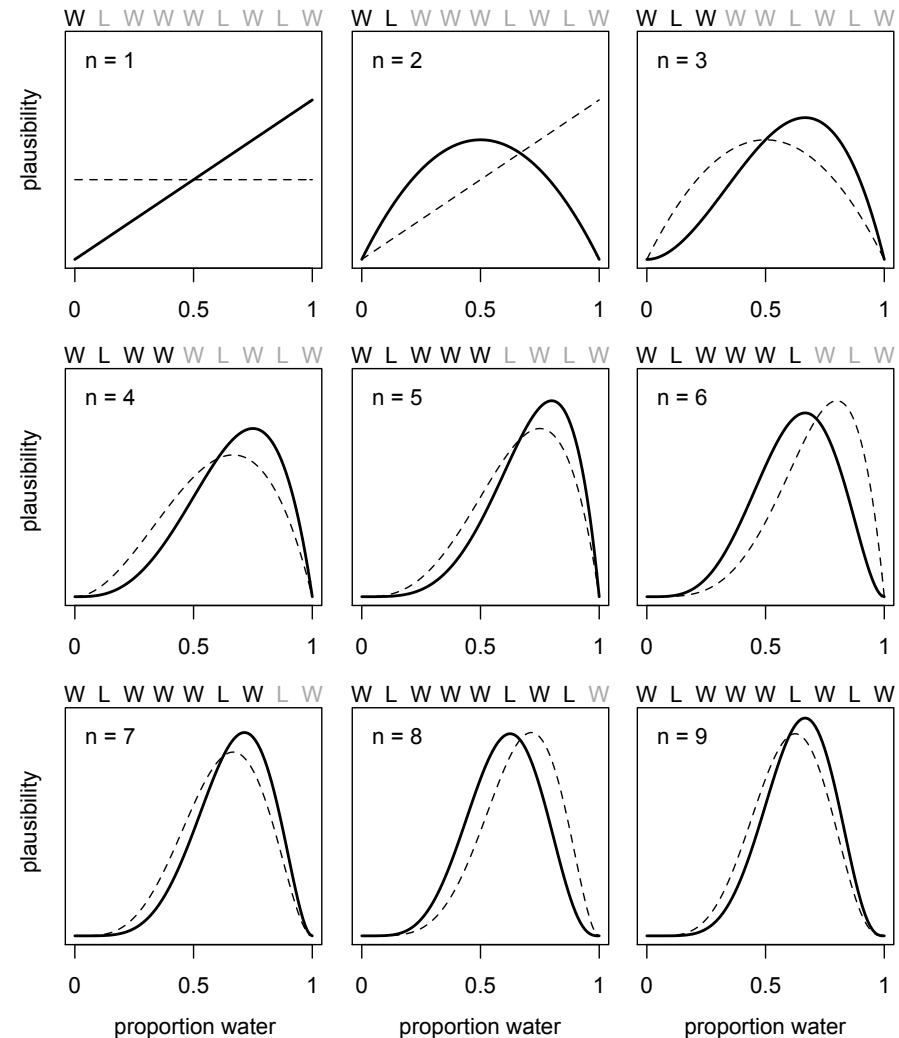


# Design > **Condition** > Evaluate

- *Bayesian updating* defines optimal learning in small world, converts *prior* into *posterior*
  - Give your golem an information state, before the data: Here, an initial confidence in each possible value of  $p$  between zero and one
  - Condition on data to update information state: New confidence in each value of  $p$ , conditional on data

# Design > Condition > Evaluate

- Data order irrelevant, because golem assumes order irrelevant
  - All-at-once, one-at-a-time, shuffled order all give same posterior
- Every posterior is a prior for next observation
- Every prior is posterior of some other inference
- Sample size automatically embodied in posterior



# Design > Condition > Evaluate

- Bayesian inference: Logical answer to a question in the form of a model

*“How plausible is each proportion of water, given these data?”*

- Golem must be supervised
  - Did the golem malfunction?
  - Does the golem’s answer make sense?
  - Does the question make sense?
  - Check sensitivity of answer to changes in assumptions

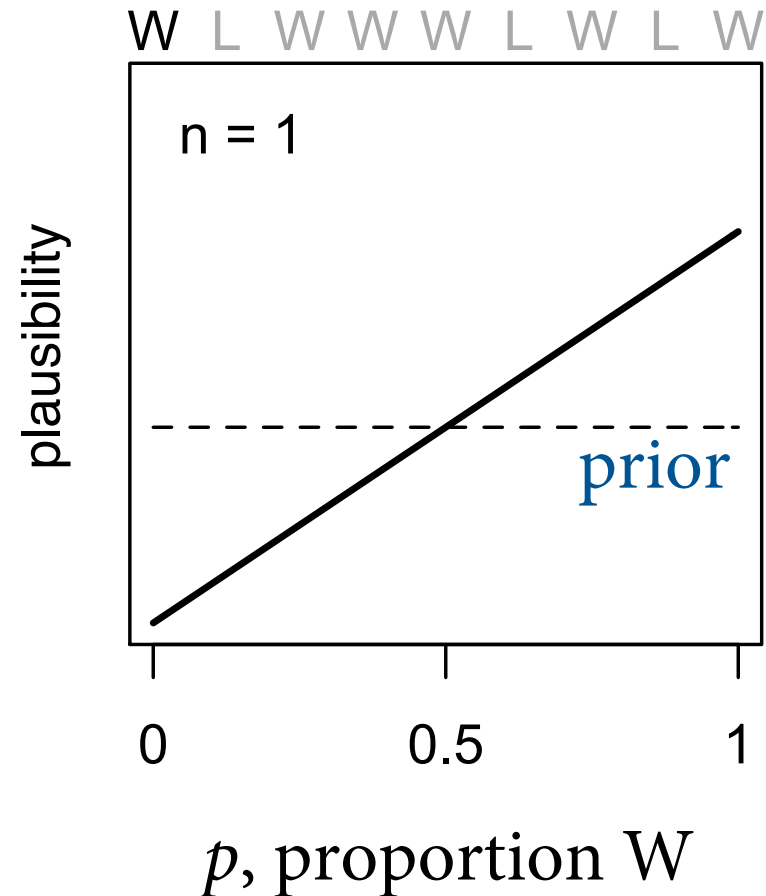


# Definition of $W$

- Relative number of ways to see  $W$ , given  $N$  and  $p$ ?
- Goal: Mathematical function to answer this question.
- The answer is a *probability distribution*.

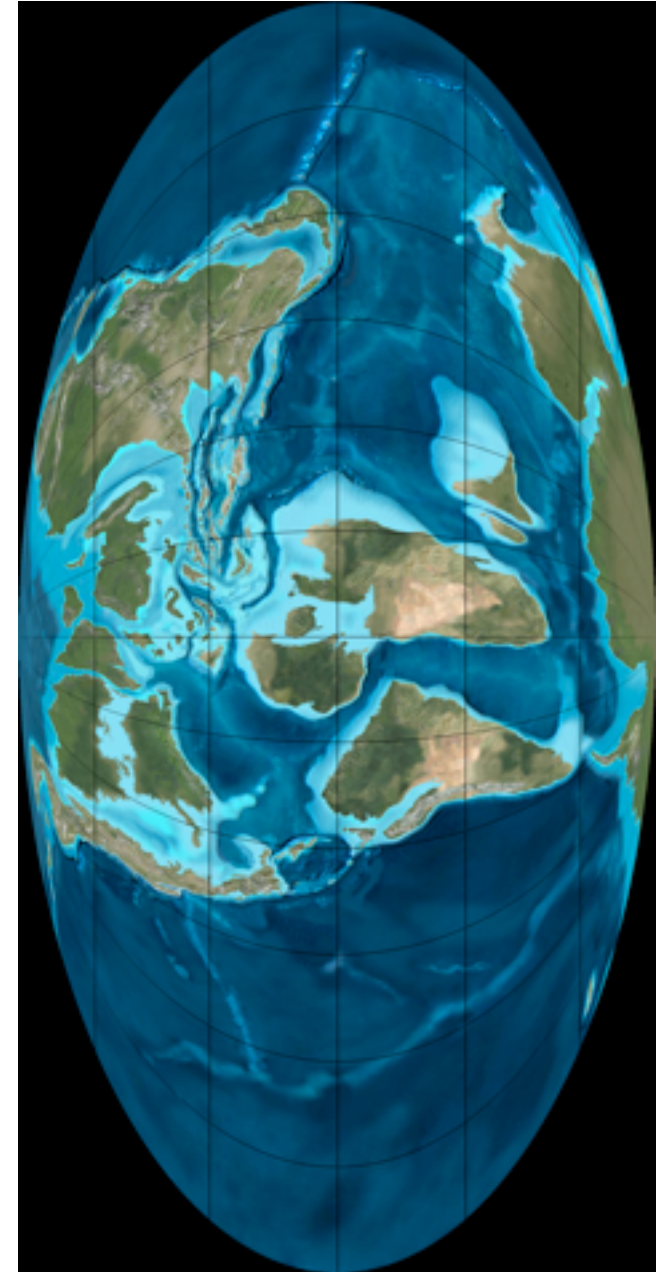
# Prior probability $p$

- What the golem believes before the data arrive
- In this case, equal prior probability 0–1
- $\Pr(W)$  &  $\Pr(p)$  define *prior predictive distribution*
- More on this later – it helps us build priors that make sense



# Prior literature

- Huge literature on choice of prior
- Flat prior conventional & bad
  - Always know something (before data) that can improve inference
  - Are zero and one plausible values for  $p$ ? Is  $p < 0.5$  as plausible as  $p > 0.5$ ?
  - There is no “true” prior
  - Just need to do better than flat
- All above equally true of likelihood



Late Cretaceous (90Mya)

# The Joint Model

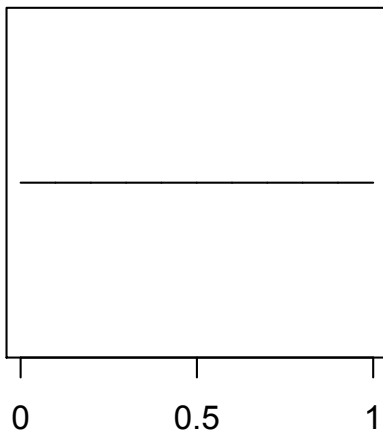
$$W \sim \text{Binomial}(N, p)$$

$$p \sim \text{Uniform}(0, 1)$$

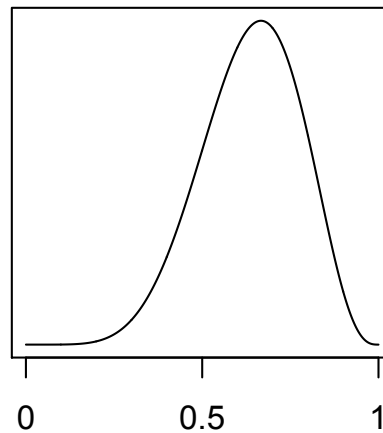
**prior**

**likelihood**

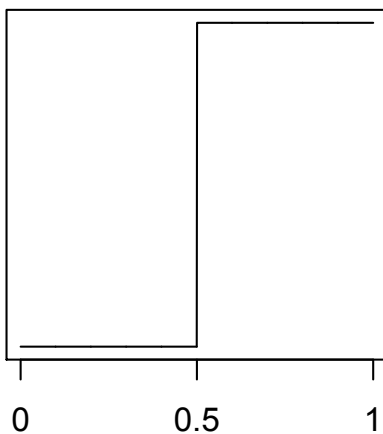
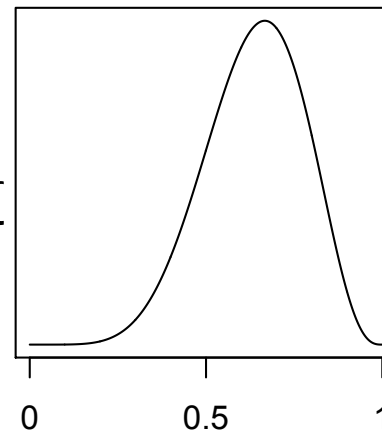
**posterior**



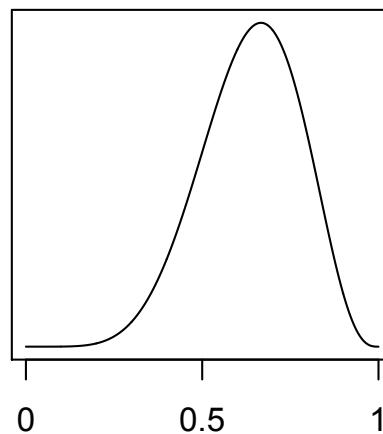
$\times$



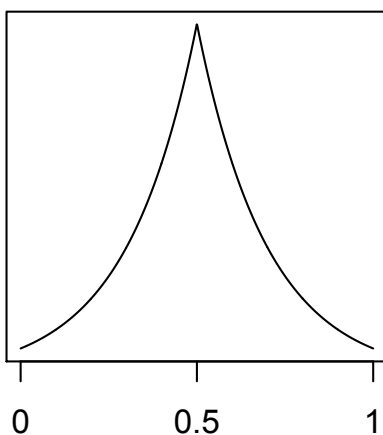
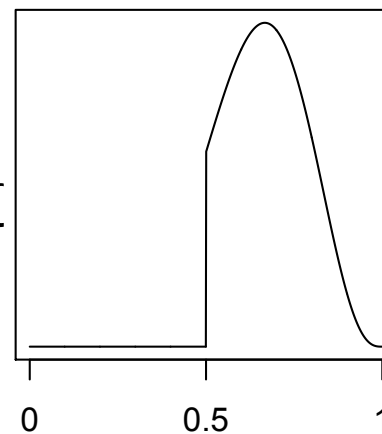
$\propto$



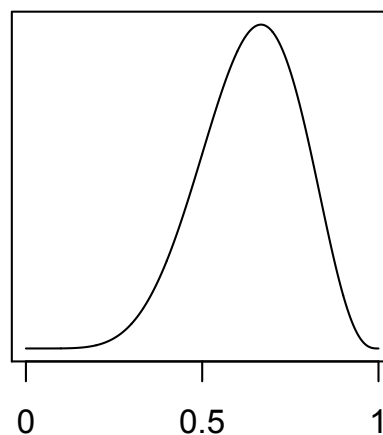
$\times$



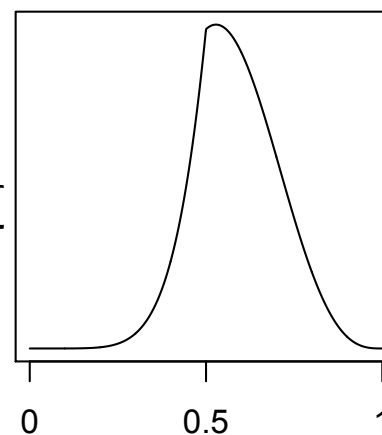
$\propto$



$\times$

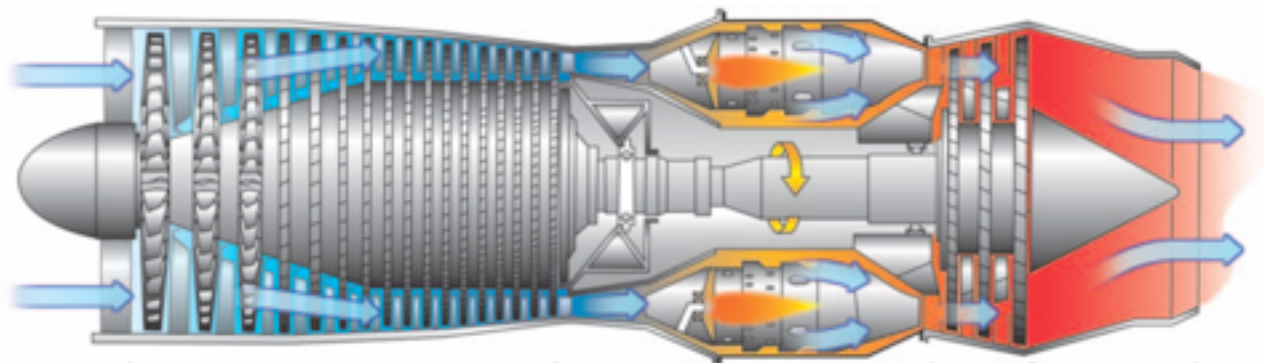


$\propto$



# Computing the posterior

1. Analytical approach (often impossible)
2. Grid approximation (very intensive)
3. Quadratic approximation (limited)
4. Markov chain Monte Carlo (intensive)



# Sampling from the posterior

- Incredibly useful to *sample randomly* from the posterior
  - Visualize uncertainty
  - Compute confidence intervals
  - Simulate observations
- MCMC produces only samples
- Above all, *easier to think with samples*
- Transforms a hard calculus problem into an easy data summary problem

# Sampling from the posterior

- Recipe:
  1. Compute or approximate posterior
  2. Sample with replacement from posterior
  3. Compute stuff from samples

# Sample from posterior

R code  
3.3

```
samples <- sample( p , prob=posterior , size=1e4 , replace=TRUE )
```

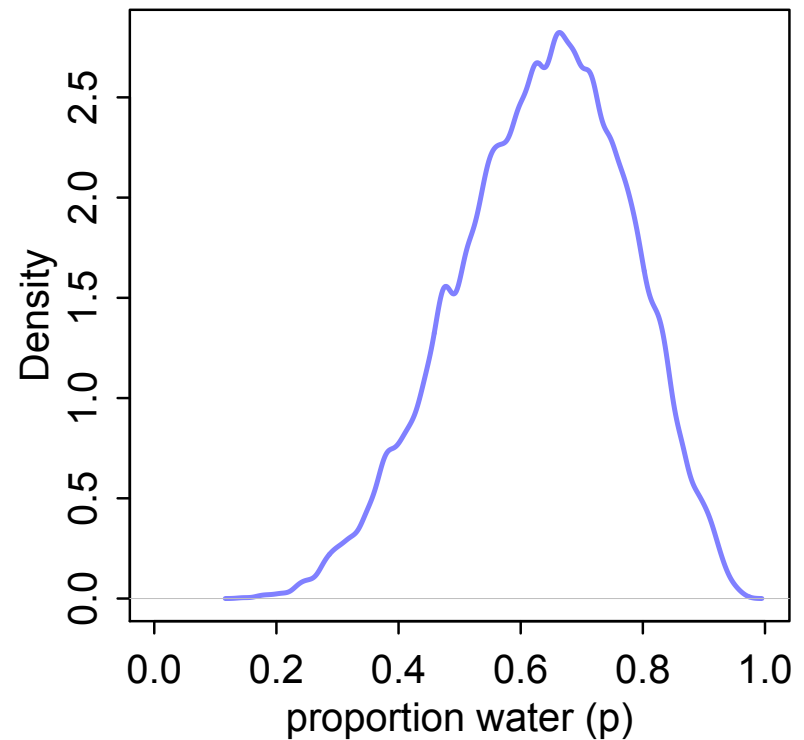
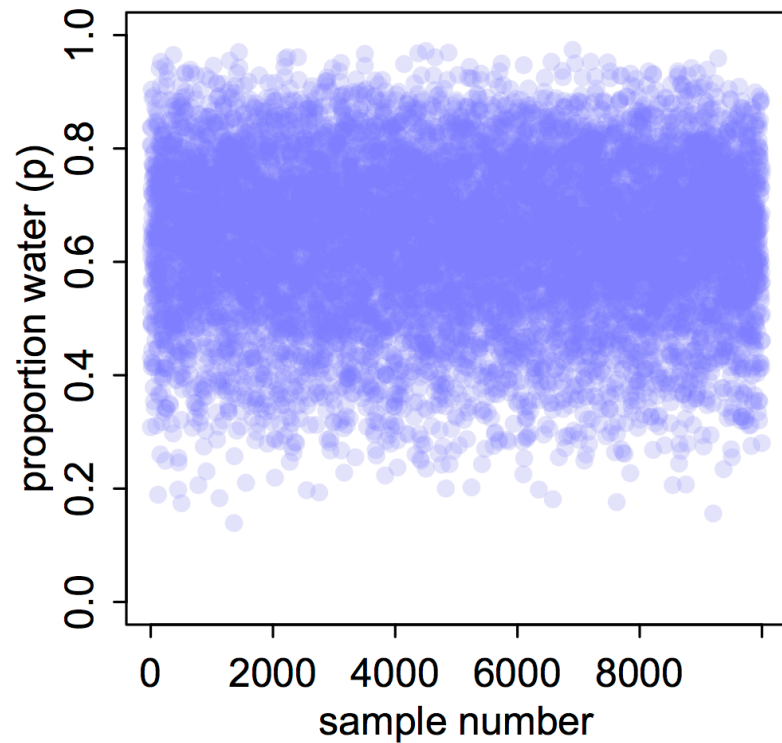


Figure 3.1

# Compute stuff

- Summary tasks
  - How much posterior probability below/above/between specified parameter values?
  - Which parameter values contain 50%/80%/95% of posterior probability? “*Confidence*” *intervals*
  - Which parameter value maximizes posterior probability? Minimizes posterior loss? *Point estimates*
- You decide the question

# Talking about intervals

- “Confidence interval”
  - A non-Bayesian term that doesn’t even mean what it says
- “Credible interval”
  - The values are not “credible” unless you trust the model & data
- How about: *Compatibility interval*
  - Interval contains values compatible with model and data as provided
  - Small World interval



<https://xkcd.com/2048/>

# Predictive checks

- Something like a *significance test*, but not
- No universally best way to evaluate adequacy of model-based predictions
- No way to justify always using a threshold like 5%
- Good predictive checks always depend upon purpose and imagination



“It would be very nice to have a formal apparatus that gives us some ‘optimal’ way of recognizing unusual phenomena and inventing new classes of hypotheses [...]; **but this remains an art for the creative human mind.**”

—E.T. Jaynes (1922–1998)